How does hourly variation in exposure to cyclists and motorised vehicles affect cyclist safety? A case study from a Dutch cycling capital

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1. Introduction

Cycling is promoted as a sustainable and healthy mode of transport, which results in an increase in bicycle use in urban areas. Increasing bicycle use comes with growing concerns about cyclist safety. This study examines how the temporal variation in the network-wide exposure to cyclists and motorised vehicles affects bicycle crash frequency. Network-wide hourly volumes of cyclists and motorised vehicles were estimated and regression models were used to identify the effect of the exposure to traffic on bicycle crashes in the city of Utrecht, a Dutch cycling capital. The results show that increasing exposure to motorised vehicles, and to a lesser extent, exposure to cyclists, increases the number of bicycle crashes on 50 km/h roads. For 30 km/h roads, no statistically significant relationship between the exposure to cyclists and bicycle crashes was found. Moreover, it was shown that cyclist crash numbers on 30 km/h roads are less sensitive to an increase in the exposure to motorised vehicles compared to cyclist crash numbers on 50 km/h roads. Furthermore, the exposure to motorised vehicles is a stronger factor affecting the increase in bicycle crashes on roads with bicycle lanes or mixed traffic conditions than on roads with separated bicycle facilities. To conclude, this study shows that road safety for cyclists needs further improvements, as cycling in cities keeps increasing.

Accordingly, the aim of this paper is to investigate how bicycle and motorised vehicle volumes affect cyclist safety on urban roads. To do this, the effect of the network-wide hourly exposure to cyclists and motorised vehicles on bicycle crash frequency was examined. That is, the total number of cyclists and motorised vehicles in the whole network for each hour of the week were estimated and used as the network-wide hourly exposure. In other words, the exposure to traffic was spatially aggregated (i.e. network-wide numbers were used) and temporally disaggregated (i.e. hourly volumes) to reveal the close relationship between volume and crash frequency more accurately. This approach allowed us to capture the safety impacts of temporal variation in the numbers of cyclists and motorised vehicles in the same network, rather than comparing differences between roadway segments which have high or low traffic volumes and based on yearly averages. The city of Utrecht in the Netherlands was chosen as the case study area considering that Utrecht has the highest bicycle usage levels in the Netherlands and is internationally known for being very bicycle friendly with a well-

Keywords:
Bicycle safety
Network-wide exposure
Temporal analysis
Bicycle infrastructure

ABSTRACT

Cycling is promoted as a sustainable and healthy mode of transport, which results in an increase in bicycle use in urban areas. Increasing bicycle use comes with growing concerns about cyclist safety. This study examines how the temporal variation in the network-wide exposure to cyclists and motorised vehicles affects bicycle crash frequency. Network-wide hourly volumes of cyclists and motorised vehicles were estimated and regression models were used to identify the effect of the exposure to traffic on bicycle crashes in the city of Utrecht, a Dutch cycling capital. The results show that increasing exposure to motorised vehicles, and to a lesser extent, exposure to cyclists, increases the number of bicycle crashes on 50 km/h roads. For 30 km/h roads, no statistically significant relationship between the exposure to cyclists and bicycle crashes was found. Moreover, it was shown that cyclist crash numbers on 30 km/h roads are less sensitive to an increase in the exposure to motorised vehicles compared to cyclist crash numbers on 50 km/h roads. Furthermore, the exposure to motorised vehicles is a stronger factor affecting the increase in bicycle crashes on roads with bicycle lanes or mixed traffic conditions than on roads with separated bicycle facilities. To conclude, this study shows that road safety for cyclists needs further improvements, as cycling in cities keeps increasing.

1. Introduction

Cycling is promoted as a sustainable and healthy mode of transport and many cities in the Global North have witnessed an increase in bicycle use (Pucher et al., 2010; Schepers et al., 2021). Increasing bicycle use in urban areas leads to a more intensely used cycling network, which can entail safety risks for cyclists (Schepers et al., 2017a). Therefore, concerns about cyclist safety have been growing as well. In the European Union, 2160 cyclists were killed in traffic in 2018 alone. It is noteworthy that the number of cyclist fatalities has remained the same since 2010, while for all other modes of transport fatalities decreased by 19%–24%. Moreover, the number of severely injured cyclists increased by 28% in the same period. The majority of these fatal and severe injury crashes occur on urban roads and often involve a motorised vehicle (Adminaité-Fodor & Jost, 2020). These figures show that it is important to examine how bicycle use and motorised vehicle use in cities affects the number of bicycle crashes.

Accordingly, the aim of this paper is to investigate how bicycle and motorised vehicle volumes affect cyclist safety on urban roads. To do this, the effect of the network-wide hourly exposure to cyclists and motorised vehicles on bicycle crash frequency was examined. That is, the total number of cyclists and motorised vehicles in the whole network for each hour of the week were estimated and used as the network-wide hourly exposure. In other words, the exposure to traffic was spatially aggregated (i.e. network-wide numbers were used) and temporally disaggregated (i.e. hourly volumes) to reveal the close relationship between volume and crash frequency more accurately. This approach allowed us to capture the safety impacts of temporal variation in the numbers of cyclists and motorised vehicles in the same network, rather than comparing differences between roadway segments which have high or low traffic volumes and based on yearly averages. The city of Utrecht in the Netherlands was chosen as the case study area considering that Utrecht has the highest bicycle usage levels in the Netherlands and is internationally known for being very bicycle friendly with a well-

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Cyclist safety is affected by the interaction between five risk factors: human factors (e.g. cycling skills, driver behaviour), vehicle-related factors (e.g. vehicle design, state of the vehicle), infrastructure factors (e.g. bicycle facilities, speed limits), traffic conditions (e.g. traffic volumes, modal split), and (built) environment factors (e.g. distance to locations, weather) (Salmon et al., 2022; Schepers et al., 2014; Twisk et al., 2013; Vandenbulcke-Plasschaert, 2011). Although all these factors play different roles in the occurrence of bicycle crashes, the aim of this paper is to delve into the effects of traffic exposure – the fundamental predictor of bicycle crashes – and to a lesser extent on infrastructure. Therefore, other influential factors are outside the scope of the study. For a broader perspective on all of these risk factors and cyclist safety, please refer to the studies by Schepers et al. (2014) and Salmon et al. (2022). In order to investigate the effects of the exposure to cyclists and motorised vehicles on bicycle crash frequency, a conceptual framework is provided in Fig. 2.1. This framework is related to a larger conceptual framework illustrating road safety for cyclists created by Schepers et al. (2014). The remainder of this section describes the variables and relationships in the conceptual framework in relation to existing literature and findings of previous studies and ends with the study hypotheses.

2.1. Network

In this study the network is considered as a single entity. This network contains the ‘three safety pillars’: road users, infrastructure and traffic (Schepers et al., 2014). Together, these are a mechanism leading to exposure to risk and, potentially, to bicycle crashes.

2.1.1. Bicycle crash frequency and exposure to risk

The aim of this study is to investigate the relationship between exposure to risk and bicycle crash frequency. The majority of bicycle safety literature examines the presence of a “safety-in-numbers effect.” This “effect” suggests that the number of bicycle crashes increases proportionally less with the increase in bicycle volume, which is called the non-linearity of risk (Elvik, 2009; Jacobsen, 2015; Schepers et al., 2014). Thus, the crash risk per cyclist is assumed to reduce when the number of cyclists on the road increases. It is argued that drivers of motorised vehicles adjust their behaviour when they expect cyclists on the road. Therefore, in this study, the focus is on bicycle crash frequency rather than on risk and safety in numbers.

2.1.2. Infrastructure

Two infrastructural aspects were considered in this study: 1) bicycle facilities, and 2) speed limit. Bicycle facilities are divided between physically separated bicycle facilities (bicycle tracks and service roads) and on-street cycling facilities (mixed traffic conditions, bicycle lanes and bicycle streets). Several studies confirmed that bicycle tracks are

Fig. 2.1. Conceptual framework for the relationships between exposure and bicycle crash frequency.
streets, and mixed traffic conditions between 50 km/h and 70 km/h, like on most distributor roads. Speed limits are above 30 km/h (Thomas–Petegem et al., 2021; Wang et al., 2019). Although the actual crash frequency on bicycle tracks may be higher (potentially due to bicycle-to-motorised vehicle collisions) because bicycle tracks attract more cyclists. Moreover, while some studies found that bicycle lanes improve safety compared to mixed traffic conditions, others found no safety difference between bicycle lanes or mixed traffic conditions, or even found increasing crash numbers after implementing bicycle lanes (DiGioia et al., 2017; Strauss et al., 2015; van Petegem et al., 2021). Another approach for separating cyclists from high motorised vehicle volumes is “unbundling”. This means that cyclists are guided through traffic-calmed areas to avoid high motorised vehicle volumes on distributor roads (Schepers et al., 2013).

The speed limit is also an important factor in cycling safety. When traffic speed in urban areas is higher, the risk of being seriously injured or having a fatal crash increases proportionally (Schepers et al., 2014). This is due to the amount of kinetic energy exchanged in a collision between a cyclist and a motorised vehicle. This finding was confirmed in a study by Aldred et al. (2018), who found that 20 mi/h (32 km/h) speed limits reduce injury risks by 21%, when compared to 30 mi/h (48 km/h) speed limits. Similarly, Wang et al. (2019) found that around 75% of all bicycle crashes in Antwerp occurred on roads with a speed limit of between 50 km/h and 70 km/h, like on most distributor roads.

### 2.2. Temporal variation in traffic and bicycle safety

Several studies included various temporal dimensions in investigating the relationship between exposure and bicycle safety. In Antwerp, the temporal dimension in bicycle safety is captured by including peak hour volumes of motorised vehicles, while the exposure to cyclists was based on the average daily bicycle volume only (Wang et al., 2019). The results show that an increase in motorised vehicle volume during peak hours leads to an increase in bicycle crashes. A study by Dozza (2017) showed that for different temporal resolutions (months of the year, days of the week, hours of the day), bicycle crashes follow the flow of cyclists. However, on weekend nights, bicycle crashes should be explained by other factors than only the exposure to cyclists, such as riding under the influence of alcohol and difference in daylight. Limitations of this study are the absence of the exposure to motorised vehicles and the use of only a small subset of count stations used as a predictor for bicycle crashes in a large area.

Both Lücke (2018) and Lücke and Wagner (2020) examined bicycle crash risk in Berlin on different temporal scales with the same approach and similar results. They used bicycle count data from a few locations and from one day per month to predict bicycle volumes throughout the whole study area based on weather data. The results suggest a declining crash risk with increasing bicycle volumes on an annual scale. The opposite was found on both a monthly and daily scale: bicycle crash risk increased with increasing bicycle volumes. This indicates a safety-in-numbers effect on an annual scale while on a finer temporal resolution a “hazard-in-numbers effect” was found. Drawbacks of this study are the exclusion of motorised vehicle volumes, as they were assumed to remain the same in the study period, and the imprecision of bicycle volume estimation due to unreliability in bicycle volume data.

Lastly, in Ottawa, Canada, Ferster et al. (2021) used the network-wide exposure to cyclists, using several temporal resolutions, to map hotspots of bicycle crashes on different categories of roads. Bicycle sports app data were used as a measure of exposure on a yearly scale, seasonal scale, daily scale, and sub-daily scale (only the peak hours). The results show that during peak hours hotspots coincide with areas which have bicycle tracks, while during off-peak hours and at the weekends, hotspots are mainly located on commercial streets, referring to multi-use paths. However, the absence of motorised vehicle volumes is a limitation in this study, as well as relying solely on bicycle sports app data, as these may be biased due to an overrepresentation of recreational cyclists (Roy et al., 2019).

A common limitation of most of the above-mentioned studies is the absence of motorised vehicle volumes and the limited use of network-wide bicycle exposure data. Furthermore, while most studies capture different temporal dimensions, only a few were able to include temporal resolutions close to the level of detail in our study. To fill these gaps, in the present study, network-wide hourly bicycle volumes and motorised vehicle volumes were used to capture short-term variation in exposure and bicycle safety. Note that the road users (Fig. 2.1) aspect is not considered in this study as the main focus is to identify network-wide variations, which makes it impossible to include the individual characteristics of cyclists. Nonetheless, it is worth mentioning that different groups of road users may be present in the network at different times of the day. For example, aging cyclists are more probable to cycle during off-peak hours, while at the weekends, during the evening, younger cyclists are assumed to be more active (Statistics Netherlands (CBS), 2017).

### Table 3.1

Descriptive statistics of variables for the included road categories in Utrecht (n = 168 h).

<table>
<thead>
<tr>
<th>Variable and road category</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Max</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Number of hourly bicycle crashes</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2015–2019</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Full network</td>
<td>3.5</td>
<td>3.2</td>
<td>14</td>
<td>590</td>
<td></td>
</tr>
<tr>
<td>50 km/h</td>
<td>2.7</td>
<td>2.6</td>
<td>0</td>
<td>11</td>
<td>447</td>
</tr>
<tr>
<td>30 km/h</td>
<td>0.9</td>
<td>1.0</td>
<td>0</td>
<td>4</td>
<td>143</td>
</tr>
<tr>
<td>50 km/h separated facilities</td>
<td>2.2</td>
<td>2.3</td>
<td>0</td>
<td>9</td>
<td>374</td>
</tr>
<tr>
<td>30 km/h separated facilities</td>
<td>0.4</td>
<td>0.7</td>
<td>0</td>
<td>4</td>
<td>48</td>
</tr>
<tr>
<td>50 km/h on-street cycling facilities</td>
<td>0.3</td>
<td>0.6</td>
<td>0</td>
<td>3</td>
<td>73</td>
</tr>
<tr>
<td>50 km/h on-street cycling facilities</td>
<td>0.6</td>
<td>0.8</td>
<td>0</td>
<td>4</td>
<td>95</td>
</tr>
<tr>
<td><strong>Hourly bicycle volume</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Full network</td>
<td>1674</td>
<td>1046</td>
<td>701</td>
<td>5521</td>
<td>281,237</td>
</tr>
<tr>
<td>50 km/h</td>
<td>1788</td>
<td>1146</td>
<td>739</td>
<td>6108</td>
<td>300,373</td>
</tr>
<tr>
<td>30 km/h</td>
<td>1456</td>
<td>862</td>
<td>628</td>
<td>4546</td>
<td>244,544</td>
</tr>
<tr>
<td>50 km/h separated facilities</td>
<td>2112</td>
<td>1411</td>
<td>837</td>
<td>7382</td>
<td>354,788</td>
</tr>
<tr>
<td>30 km/h separated facilities</td>
<td>3128</td>
<td>2416</td>
<td>834</td>
<td>11856</td>
<td>525,451</td>
</tr>
<tr>
<td>50 km/h on-street cycling facilities</td>
<td>1192</td>
<td>666</td>
<td>557</td>
<td>3762</td>
<td>200,197</td>
</tr>
<tr>
<td>50 km/h on-street cycling facilities</td>
<td>1216</td>
<td>645</td>
<td>599</td>
<td>3649</td>
<td>204,268</td>
</tr>
<tr>
<td><strong>Hourly motorised vehicle volume</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Full network</td>
<td>3114</td>
<td>2005</td>
<td>199</td>
<td>6714</td>
<td>253,170</td>
</tr>
<tr>
<td>50 km/h</td>
<td>3931</td>
<td>2523</td>
<td>260</td>
<td>8418</td>
<td>660,393</td>
</tr>
<tr>
<td>30 km/h</td>
<td>1548</td>
<td>1015</td>
<td>81</td>
<td>3447</td>
<td>260,043</td>
</tr>
<tr>
<td>50 km/h separated facilities</td>
<td>4822</td>
<td>3100</td>
<td>320</td>
<td>10427</td>
<td>810,160</td>
</tr>
<tr>
<td>30 km/h separated facilities</td>
<td>2070</td>
<td>1288</td>
<td>121</td>
<td>4290</td>
<td>347,712</td>
</tr>
<tr>
<td>50 km/h on-street cycling facilities</td>
<td>2290</td>
<td>1463</td>
<td>147</td>
<td>4720</td>
<td>384,075</td>
</tr>
<tr>
<td>30 km/h on-street cycling facilities</td>
<td>1473</td>
<td>977</td>
<td>74</td>
<td>3326</td>
<td>247,473</td>
</tr>
<tr>
<td><strong>Total road length in km</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Full network</td>
<td>– – – –</td>
<td>321.9</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50 km/h</td>
<td>– – – –</td>
<td>211.6</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>30 km/h</td>
<td>– – – –</td>
<td>110.3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50 km/h separated facilities</td>
<td>– – – –</td>
<td>137.1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>30 km/h separated facilities</td>
<td>– – – –</td>
<td>13.8</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50 km/h on-street cycling facilities</td>
<td>– – – –</td>
<td>74.5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>30 km/h on-street cycling facilities</td>
<td>– – – –</td>
<td>96.5</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Separated facilities include physically separated bicycle tracks, adjacent to roads and service roads; on-street cycling facilities include bicycle lanes, bicycle streets, and mixed traffic conditions.
2.3. Study hypotheses

Based on the literature review and findings of previous studies, this paper sought to test the following hypotheses:

1. The number of bicycle crashes may increase less than proportionally with the increase in bicycle traffic (Elvik, 2009; Wegman et al., 2012).
2. Peak hours on weekdays have the highest levels of exposure; thus, a higher crash frequency can be expected during peak hours compared to off-peak hours (Ferster et al., 2021; Wang et al., 2019).
3. After correcting for exposure, higher numbers of bicycle crashes are expected to happen at night than during the day (Dozza, 2017).
4. Roads with higher speeds might be associated with more serious bicycle crashes compared to roads with lower speeds (Aldred et al., 2018; Wang et al., 2019).
5. Roads with separated bicycle facilities are safer than roads with bicycle lanes or mixed traffic conditions (DiGioia et al., 2017; van Petegem et al., 2021).

3. Data

Table 3.1 shows a summary of all the variables and road categories used in this study. The hourly bicycle crashes were composed from five years of crash data, based on the aggregated numbers in the hour of occurrence, during the week. In the table, the average number of crashes is calculated over the aggregated hourly crash numbers. Thus, on 50 km/h roads, on average there are 2.7 crashes per hour in the five years of aggregated crash data. Similarly, the average bicycle and motorised vehicle volumes show the average of the aggregated number of vehicles passing, per kilometre, in one hour. The total values show the aggregated crash numbers and the aggregated volumes for all 168 h of the week. Sections 3.1 - 3.4 provide detailed descriptions of the data.

Although 30 km/h roads with separated bicycle facilities have the lowest total road length, per kilometre they attract more cyclists compared to the other categories. Moreover, 50 km/h roads with separated bicycle facilities attract more motorised vehicles per kilometre. However, while cyclists exceed motorised vehicles on 30 km/h roads with separated bicycle facilities, the contrary is true for the 50 km/h roads with separated bicycle facilities. Lastly, more bicycle crashes occurred on 50 km/h roads compared to 30 km/h roads; 50 km/h roads with separated bicycle facilities have more bicycle crashes compared to 30 km/h roads with separated bicycle facilities and both of the categories with on-street cycling facilities.

3.1. Road categories

The road categories were obtained from the network of the Bicycle Route Planner, provided by the Dutch Cyclists’ Union (Fietsersbond) (Dutch Cyclists’ Union, 2020). This network includes all roads and bicycle facilities in the Netherlands, which provides a wide range of information. The most relevant variables for this study were the length of road sections, road levels and road types. The speed limit was unavailable in this data set. This information was gathered from another data set, which is publicly available and provided by the Dutch national road authority (Rijkswaterstaat) (Rijkswaterstaat, 2020b). To avoid potential errors in the data, the speed limits were validated by using Google Street View. The “road types” variable contains valuable information about bicycle infrastructure types. To characterise road types, two kinds of bicycle infrastructure were distinguished: 1) on-street facilities, and 2) separated facilities. The on-street facilities contain bicycle lanes, bicycle streets and mixed traffic conditions; the separated facilities contain physically separated bicycle tracks, adjacent to roads and service roads. Furthermore, different speed limits were used to characterise the road categories: 50 km/h distributor roads and 30 km/h access roads. The division in road categories is based on differences in safety between types of bicycle facilities, safety between speed limits, and the layout of the infrastructure.

3.2. Crash data

The crash data were retrieved from the Database of Registered Crashes in the Netherlands (BRON) and are based on police reports (Rijkswaterstaat, 2020a). Note that the analysed crash data does not illustrate the full size of the safety problem for cyclists in Utrecht due to underreporting of bicycle-to-bicycle crashes and single-bicycle crashes by the police. This may influence the results of this study, but more inclusive data are unavailable for the study area. Thus, the bicycle crashes in this study are all injury and fatal crashes that involved at least one cyclist, which occurred between 2015 and 2019 on the road categories that were studied, and which were reported by the police. Injury in this study means that there was at least a light injury resulting from a crash and also includes crashes leading to emergency care and inpatients. Both road section crashes and intersection crashes were included; intersection crashes were included as they are part of the total network.

In total, 590 bicycle crashes were used, of which 8 were fatal and 572 were injury crashes. The majority of these crashes are bicycle-to-motorised vehicle crashes (452 crashes). For the other 138 crashes, it is unknown if a motorised vehicle was involved and they are indicated in the crash data as bicycle-to-bicycle crashes, single-bicycle crashes, or bicycle-pedestrian crashes. Although these crash numbers are not the actual numbers, these crashes are included as the study tries to find out what happens to the number of bicycle crashes in a network when total network exposure increases. Moreover, interactions with other road users indirectly play a large role in single-bicycle crashes, which makes the exposure to other road users also applicable in these crashes (Hertach et al., 2018; Myhrmann et al., 2021; Valkenberg et al., 2017).

For comparison, a study by Weijermars et al. (2016) tried to estimate the total number of seriously injured road users in the Netherlands between 2000 and 2011 by linking the police reported data (BRON) to hospital registrations. 41% of the hospital registrations could be
Fig. 3.2. Bicycle and motorised vehicle (MV) measurement locations.

Fig. 4.1. Map of the road categories in the study area: Utrecht, the Netherlands.
across the Netherlands used a smartphone app to track their routes. Fig. 3.1 shows the lengths of the trips made in the city of Utrecht. The week in 2016, a sample of approximately 29,000 voluntary cyclists and 2017, and it was organised by the Dutch Cyclists data set, collected for one week in September in the years 2015, 2016 and 2017, and it was organised by the Dutch Cyclists’ Union. During this week in 2016, a sample of approximately 29,000 voluntary cyclists across the Netherlands used a smartphone app to track their routes. Fig. 3.1 shows the lengths of the trips made in the city of Utrecht. The FTW data is used to represent the temporal variation (hours of the day) in bicycle volumes for the Utrecht cycling network. Second, the Municipality of Utrecht provided an extensive data set containing bicycle counts from sixteen permanent count stations for the years 2015 until 2019 (Municipality of Utrecht, 2020). The count data provides hourly intervals through the whole year. Fig. 3.2 shows the locations of the ten permanent count stations used in this study.

3.3. Bicycle volume data

Two data sets were used to estimate the network-wide hourly exposure to cyclists (see Section 4.2 for the estimation of volumes). First, data from the Dutch Bicycle Counting Week (Fietstelweek, abbreviated as FTW) was used (Cycling Intelligence, 2021). This is a large GPS-based data set, collected for one week in September in the years 2015, 2016 and 2017, and it was organised by the Dutch Cyclists’ Union. During this week in 2016, a sample of approximately 29,000 voluntary cyclists across the Netherlands used a smartphone app to track their routes. Fig. 3.1 shows the lengths of the trips made in the city of Utrecht. The FTW data is used to represent the temporal variation (hours of the day) in bicycle volumes for the Utrecht cycling network. Second, the Municipality of Utrecht provided an extensive data set containing bicycle counts from sixteen permanent count stations for the years 2015 until 2019 (Municipality of Utrecht, 2020). The count data provides hourly intervals through the whole year. Fig. 3.2 shows the locations of the ten permanent count stations used in this study.

3.4. Motorised vehicle volume data

Motorised vehicles in this study include cars, light goods vehicles, heavy goods vehicles and buses. Buses are included, as some roads have a separate bus lane. To derive hourly motorised vehicle volumes, two data sets were used. First, hourly motorised vehicle count data was used, which were collected at intersections and other locations with cameras or induction loops. This resulted in an average hourly motorised vehicle flow for a large part of the roads in the network of the transport model. The data is divided between both directions and the sum of these directions was used as volume per road section. Second, for the missing sections in the hourly data set, the transport model from the Municipality of Utrecht was used to estimate these hourly volumes (see Section 4.2 for the estimation of volumes). Fig. 3.2 shows the measured and unmeasured sections, as well as the locations of the cameras.

4. Methodology

4.1. Study area

The study area is the Dutch city of Utrecht, which had a population size of 360,000 in 2020. It is the fourth largest city in the Netherlands and one of the most bicycle-oriented Dutch cities. Furthermore, in 2015, over 40% of short trips (from 1 km to 7 km) were made by bicycle, while for cars this was 22% (Jonkeren et al., 2019). Fig. 4.1 shows a map of the road network in Utrecht where the studied road categories are highlighted. As can be seen on the map, Utrecht has a very dense road network, making it suitable for cycling. Altogether, this makes Utrecht a good representation of the Dutch “cycling culture”, which positively influences the level of safety (Scheper et al., 2017b). However, as Dutch crash statistics show, the number of cyclists involved in fatal and severe crashes increased in the past ten years and their share in these crashes is the biggest compared to other road users (Aarts et al., 2020). The increasing number of bicycle crashes, the high levels of bicycle use, its well-designed and dense cycling network, and the high level of urbanisation make Utrecht an interesting case to examine the impact of the exposure to cyclists and motorised vehicles on bicycle safety.

4.2. Estimating network-wide hourly exposure

To measure the network-wide exposure to cyclists, bicycle volumes for all road sections of the network are needed. For this purpose, hourly bicycle count data from permanent count stations and from the Fietstelweek (FTW) were used. In order to control whether the FTW is an appropriate proxy of actual counts, the hourly FTW data were compared with counts at the permanent count stations. It was observed that the FTW data from 2016 show an hourly flow pattern similar to the permanent count stations. Therefore, the FTW data from 2016 were used as a predictor for the estimation of the hourly volumes in the network. The only conspicuous difference between the permanent count stations and the FTW data are the off-peak hours on weekdays. This is because count stations count all the cyclists, whereas the FTW misses a share of cyclists, as this GPS-based data do not include all cyclists because some groups of cyclists may not have participated in the FTW.

To estimate network-wide, hourly bicycle volumes, first a Simple Linear Regression (SLR) model was fitted. However, the predictive performance of SLR was unsatisfactory. Therefore, a Support Vector Regression (SVR) model with better predictive capabilities was used. This model proved to be a suitable approach to predict traffic volumes in earlier studies (Hong, 2011; Lippi et al., 2013). The purpose of SVR is to
To find the best fitting hyperplane, similar to a regression line, and to find the right balance between model complexity and prediction error ($\epsilon$). For bicycle volume prediction this means that the accuracy of the predictions is dependent on the size of $\epsilon$. It is therefore important to define the “best” $\epsilon$ in the model tuning process, as better estimated bicycle volumes eventually determine the coefficients of bicycle volume in the crash prediction models. Please refer to Awad and Khanna (2015) and Smola and Schölkopf (2004) for details of the SVR method. For the data in this study, a non-linear SVR model with a Radial Basis Function (RBF) kernel produced the best fit (Fig. 4.2). This kernel transforms the non-linear data into a high-dimensional feature space where the hyperplane is theoretically linear. Although the model still slightly overpredicts during night hours (00:00–06:00), the other two models led to a less accurate fit.

For motorised vehicles a large share of the road sections had hourly data available from induction loops and cameras. For the unmeasured sections, these hourly volumes were estimated. The average relative hourly volumes of the sections that were available were used to calculate the hourly volumes of the unmeasured sections. The relative hourly volumes were multiplied by the average weekly motorised vehicle volume for each road section that had missing hourly data. These weekly averages were retrieved from the municipal transport model.

### 4.3. Aggregating hourly data

As the interest of this study is hourly variation in bicycle crashes, and modelling this variation, the total network exposure for each hour of the week was estimated. To obtain these aggregated hourly volumes, the hourly bicycle volume and motorised vehicle volume from each road section was divided by the total road length of the corresponding road category, which were then aggregated. Crashes were also aggregated at each hour of the week, based on their occurrence time, resulting in an hourly bicycle crash frequency. To illustrate, Fig. 4.3 shows the hourly variation in bicycle volume, motorised vehicle volume and bicycle crash frequency for the full network. The figure gives a first impression of the fact that when the total network exposure increases, bicycle crashes increase as well.

### 4.4. Bicycle crash frequency analysis

To relate the exposure to cyclists and motorised vehicles to bicycle crash numbers, a crash frequency analysis was applied. As crashes numbers are non-negative integer counts, a regression model capable of analysing count data should be used for this. While a Poisson model is mostly used when the data is not over-dispersed, most crash data should be considered over-dispersed. A model capable of handling over-dispersion is the Negative Binomial (NB) regression model and this model is therefore more suitable to analyse crash data (Lord & Manering, 2010). The expected number of crash counts in the NB model is written as:

$$\lambda_i = \exp(\beta X_i + \epsilon_i)$$  \hspace{1cm} (1)$$

where $\lambda_i$ is the expected crash frequency at hour, $X_i$ is a vector of predictors, $\beta$ is a vector of estimable parameters and $\epsilon_i$ is the Gamma-distributed error term (Lord & Manering, 2010).

The final crash model was developed as a multiplicative model (Hauer, 2004). In such models, the effect of the predictors that influence crash predictions is better denoted by multiplicative factors compared to additive factors. The final model for the present study is formulated as follows:

$$E(Y) = L \cdot V_{1i}^{a1} \cdot V_{2i}^{a2} \cdot \exp(d_0 + a_3D)$$  \hspace{1cm} (2)$$

where $E(Y)$ is the expected bicycle crash frequency, $L$ is the total road length in kilometres, $V_1$ is the hourly exposure to cyclists, $V_2$ is the hourly exposure to motorised vehicles, D is the dummy variable indicating morning/day (06:00–18:00) with evening/night (18:00–06:00) as reference category, and $a_0, a_1, a_2,$ and $a_3$ are the estimated coefficients.

As the unit of analysis is time, temporal autocorrelation may affect the results. To control if the hours of the week are correlated, a temporal weights matrix was created where every hour of the week was related to the hour before and after (a temporal contiguity). This temporal weights matrix was used to calculate a temporal Moran’s I index. Table 4.1 shows some degree of temporal autocorrelation on the residuals of few of the NB regression models, especially in the model for 30 km/h roads with separated bicycle facilities. The models with temporal autocorrelation were also the models which performed less successfully compared to the models without temporal autocorrelation. Although this may affect the goodness of fit of the models, it only has a small effect on the estimates of the variable coefficients. It was therefore decided to proceed with the NB regression model in Equation (2) and leave the temporal autocorrelation out of the analysis.

| Table 4.1 |
|---|---|
| Hours of the week Full network | 0.01 | 0.18 |
| Hours of the week 50 km/h | 0.04 | 0.14 |
| Hours of the week 30 km/h | 0.21 | 0.06 |
| Hours of the week 50 km/h separated | 0.09 | 0.11 |
| Hours of the week 30 km/h on-street | 0.00 | 0.24 |
| Hours of the week 50 km/h on-street | 0.42 | –0.00 |
| Hours of the week 30 km/h on-street | 0.30 | 0.03 |

Fig. 4.3. Hourly variation in bicycle volumes, motorised vehicle volumes, and bicycle crashes. *Black bars.

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5. Results

5.1. Bicycle safety analysis

To estimate bicycle crash frequency, seven Negative Binomial (NB) regression models were fitted; one model for every road category: the full network, 50 km/h roads, 30 km/h roads, 50 km/h roads with separated bicycle facilities, 30 km/h roads with separated bicycle facilities, 50 km/h roads with on-street cycling facilities, and 30 km/h roads with on-street cycling facilities. Both the log of the hourly exposure to cyclists and the log of the hourly exposure to motorised vehicles were used, as well as a dummy variable morning/day (06:00–18:00) as predictors for the models. Table 5.1 presents the results.

The results show that for the full network, for 50 km/h roads, and for 50 km/h road with a separated bicycle facility the exposure to cyclists is a significant positive predictor. This means that during hours with increased exposure to cyclists, the number of bicycle crashes increases as well. Furthermore, the coefficients of the exposure to cyclists are lower compared to the exposure to motorised vehicles. This suggests that during hours where the total network exposure increases, motorised vehicles are a stronger factor for the increase of bicycle crashes than cyclists are. For 50 km/h roads with on-street cycling facilities, and all different types of 30 km/h roads, the models were unable to show a significant relationship between the exposure to cyclists and bicycle crash frequency. For these categories, it is impossible to conclude that the exposure to cyclists has a considerable effect on crash frequency. In addition, the value of the coefficients of the exposure to cyclists significantly differs from 1.0. A coefficient value lower than 1.0 implies a non-linear relationship, meaning that an increase in exposure to cyclists would lead to a less than proportional increase in bicycle crashes.

For the exposure to motorised vehicles, the results show significant positive coefficients for all but one road category, meaning that during hours with increased exposure to motorised vehicles, bicycle crash frequency increases as well. Moreover, the size of the coefficients is larger on both 50 km/h and 30 km/h roads with on-street cycling facilities than on other categories; thus, bicycle crashes increase more on these roads when exposure to motorised vehicles increase than on the other categories. Furthermore, the models show that the exposure to motorised vehicles is more linearly related to bicycle crashes compared to the exposure to cyclists, as coefficients are closer to 1.0. For comparison, Fig. 5.1 illustrates the difference between the coefficients of the exposure to cyclists and the exposure to motorised vehicles per road category.

Table 5.1
Results of the Negative Binomial regression models for the effects of exposure variables on bicycle crash frequency.

<table>
<thead>
<tr>
<th></th>
<th>Full network</th>
<th>50 km/h</th>
<th>30 km/h</th>
<th>50 km/h separated</th>
<th>30 km/h separated</th>
<th>50 km/h on-street</th>
<th>30 km/h on-street</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exposure to cyclists</td>
<td>0.39***</td>
<td>0.41***</td>
<td>-0.26</td>
<td>0.70***</td>
<td>0.82***</td>
<td>0.31***</td>
<td>0.98***</td>
</tr>
<tr>
<td>Exposure to motorised vehicles</td>
<td>0.80***</td>
<td>0.84***</td>
<td>-0.60</td>
<td>-0.26</td>
<td>-0.37</td>
<td>-0.46</td>
<td>-0.75***</td>
</tr>
<tr>
<td>Morning/Day (06:00–18:00)</td>
<td>-0.38***</td>
<td>-0.30</td>
<td>-0.60</td>
<td>-0.26</td>
<td>-0.37</td>
<td>-0.46</td>
<td>-0.75***</td>
</tr>
<tr>
<td>AIC</td>
<td>665.66</td>
<td>599.83</td>
<td>382.36</td>
<td>556.06</td>
<td>227.07</td>
<td>273.18</td>
<td>313.10</td>
</tr>
<tr>
<td>Degrees of freedom</td>
<td>164</td>
<td>164</td>
<td>164</td>
<td>164</td>
<td>164</td>
<td>164</td>
<td>164</td>
</tr>
<tr>
<td>Deviance</td>
<td>192.28</td>
<td>186.38</td>
<td>165.62</td>
<td>180.09</td>
<td>126.00</td>
<td>137.41</td>
<td>153.90</td>
</tr>
<tr>
<td>50 km/h</td>
<td>12.46*</td>
<td>11.87*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: ***p < 0.001; **p < 0.01; *p < 0.05; p < 0.1; θ = overdispersion parameter; standard errors are given in round brackets; confidence intervals are given in square brackets.

Fig. 5.1. Difference between exposure to cyclists and motorised vehicles. **Hollow shapes are not significant.
category.

Finally, morning/day (06:00–18:00) seemed to be an important negative predictor for bicycle crashes for most of the road categories. Negative in this case means that, after correcting for exposure, fewer bicycle crashes occur during the morning and day compared to the reference category evening/night (18:00–06:00).

5.2. Model performance

In order to demonstrate how well the models predict the number of bicycle crashes, Fig. 5.2 and Figs. A.1 - A.6 in the Appendices have been included. These figures show the predicted crashes (the blue dots) and their 68% prediction intervals (the light red area). For every road category, the model predicts more crashes in the peak hours (weekdays 07:00–09:00 and 16:00–19:00) than off-peak hours. Furthermore, the models predict the lowest number of crashes during night times. The prediction intervals also differ among the road categories: for the 30 km/h roads, roads with on-street cycling facilities, and 30 km/h roads with separated bicycle facilities, the prediction intervals are larger than for the other models. This can be seen on the larger red area around the predicted crashes. Due to less data for these road categories, there are larger uncertainties around the predicted crashes in these models.

To further evaluate the predictive capabilities of the models, Fig. 5.3 and Figs. B.1 - B.6 in the Appendices have been included. These figures illustrate: A) the actual crashes, shown as green dots and the predicted crashes, shown as red triangles, and B) the difference between the actual

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*Fig. 5.2.* Predicted bicycle crashes and 68% prediction intervals for the full network.

*Fig. 5.3.* Difference between actual crashes and predicted crashes for the full network.
and predicted. The model either underpredicts (the difference is green) or overpredicts (the difference is red). For the full network, in Fig. 5.3, the model underpredicts during the peak hours, to some extent. This is especially visible on the first three days of the week, whereas other days are more accurate. The other models show similar patterns, even though some hours with a low number of actual crashes were slightly overpredicted. This overprediction in hours with low actual crashes is a result of using a log-transformed model, which prevents the outcome variable to be equal to zero. These findings show that the models perform well in predicting bicycle crashes during the hours of the week, despite some underprediction during the peak hours on Monday, Tuesday and Wednesday, and some overprediction in hours with low actual crash frequencies.

6. Discussion

6.1. Bicycle safety analysis

6.1.1. Exposure and bicycle crashes

The increase in bicycle crashes as a result of increased exposure to cyclists was also found in a study in Stockholm (Dozza, 2017). Similarly, it was found in another study that an increase in the exposure to motorised vehicles leads to more bicycle crashes, albeit with a lower effect compared to the results in our study (Wang et al., 2019). Moreover, the non-linear relationship between the increasing exposure to cyclists and bicycle crashes observed in this study and the safety-in-numbers effect were examined in previous studies (Aldred et al., 2019; Carlson et al., 2019; Jacobsen, 2015; Kaplan & Prato, 2015). However, a decline in bicycle crash risk in the Netherlands does not always imply a safety-in-numbers effect due to their well-designed cycling network, high levels of cycling, and cyclist-aware drivers (Schepers et al., 2017b; Wegman et al., 2012).

6.1.2. Temporal variation in bicycle crashes

The results show that bicycle crash frequency varies per hour. Hours with a higher exposure to cyclists and motorised vehicles, the peak hours, were found to have more bicycle crashes than the off-peak hours. This is in line with studies showing increased number of bicycle crashes during the peak hours (Ferster et al., 2021; Kim et al., 2007; Wang et al., 2019). Moreover, a difference in crash frequency between morning/day (06:00–18:00) and evening/night (18:00–06:00) was also shown. While crashes during daytime can be explained by exposure, during the evening and night, crashes can hardly be explained by exposure. Although the population of cyclists differs during the evening and night, especially due to the absence of older cyclists (Statistics Netherlands (CBS), 2017), after correcting for exposure, there are still more bicycle crashes resulting in injury occurring between 18:00 and 06:00. It is expected that other factors play a role in this case. This might be, for example, the difference between daylight and no daylight or, something which plays a role on weekend nights: cycling (or driving) under the influence of alcohol or other substances (Dozza, 2017; Kim et al., 2007).

6.1.3. Infrastructure: Speed limits

In this study, the model outcomes did not show a statistically significant relationship between the exposure to cyclists and bicycle crashes on 30 km/h roads. Moreover, it was shown that cyclist crash numbers on 30 km/h roads are less sensitive to an increasing exposure to motorised vehicles compared to cyclist crash numbers on 50 km/h roads. However, it is difficult to compare these road categories as, besides speed limits, also the levels of exposure and the layout of these roads are different. Nevertheless, the results are in line with studies showing that higher speeds lead to a larger number of severe bicycle crashes (Schepers et al., 2014). Furthermore, as the 50 km/h roads in this study are distributor roads, they attract more cyclists and motorised vehicles compared to 30 km/h roads and have more connections to other streets. This leads to more complexity due to more cross overs by cyclists and more turning vehicles, resulting in increased encounters between cyclists and motorised vehicles (Vandenbulcke et al., 2014). Aldred et al. (2018) had similar results: they argue that residential roads are safer for cyclists compared to other road types due to lower motorised vehicle volumes, higher bicycle volumes and lower speed limits. Lastly, these results support the concept of unbundling, as presented in the work by Schepers et al. (2013). They conclude that it is better to guide cyclists through traffic-calmed areas and to avoid having cyclists ride along distributor roads.

6.1.4. Infrastructure: Bicycle facilities

The model results show that bicycle crashes increase during hours with an increased exposure to cyclists and motorised vehicles on 50 km/h roads with separated bicycle facilities. An explanation for this result might be that 50 km/h roads with separated bicycle facilities attract more cyclists and motorised vehicles, which eventually leads to more bicycle crashes. Additionally, crossing over distributor roads from a separated bicycle facility is indicated as a risk increasing factor by Vandenbulcke et al. (2014). On 30 km/h roads with separated bicycle facilities, none of the coefficients are significant, meaning that no relationship was found between exposure and bicycle crashes. This is probably the result of specific characteristics of these roads in the case study area. That is, only a few kilometres of this road category exist and they include bus lanes with separated bicycle facilities. For both 50 km/h and 30 km/h roads with on-street cycling facilities, the results are similar. No relationship between the exposure to cyclists and bicycle crashes was found, while bicycle crashes increase when the exposure to motorised vehicles increases. The coefficient of the exposure to motorised vehicles for both of these categories is higher compared to the other categories. This indicates that it is less safe for cyclists to ride on roads with either bicycle lanes or mixed traffic conditions and suggests that mixing cyclists with motorised vehicles leads to more bicycle crashes compared to separating cyclists from motorised vehicles. These results support findings in earlier studies (DiGioia et al., 2017; van Petegem et al., 2021).

6.2. Limitations and future research directions

One of the limitations of this study is that the crash prediction models are highly dependent on the bicycle volume predictions, which in turn are dependent on the quality of bicycle volume data. While high quality count data from permanent count stations was used, the GPS tracking data set is from one week only. Moreover, the count stations were mainly located on 50 km/h roads with separated bicycle facilities and a few on 30 km/h roads with separated bicycle facilities, at locations where a lot of cyclists pass. In this way, the predictions on 50 km/h and 30 km/h roads with on-street cycling facilities may be biased. It could be beneficial to distribute the count stations more evenly throughout the city, which could provide a more complete picture of network-wide bicycle volumes. Nevertheless, the bicycle volume data used is still very high quality with a high temporal resolution, compared to data used in previous studies. Although the present study used a very accurate model, it still slightly overpredicts bicycle volumes during the night and underpredicts extreme volumes during peak hours. This potentially affects the size of the coefficients in the NB models. For example, for 30 km/h roads with separated bicycle facilities no evidence was found. This
might be because they are safer or because bicycle volumes were less accurately predicted. Therefore, future studies should expand the investigation of 30 km/h roads.

It is also worth mentioning that the crash data are based on police reports, which commonly suffer from underreporting. Especially cyclists are affected by the problem of underreporting compared to other modes of transport, which makes underreporting selective. While the more severe crashes and crashes involving a motorised vehicle are mostly well-reported, this is not the case for crashes involving cyclists and the less severe crashes. This is especially true for bicycle-to-bicycle crashes and single-bicycle crashes, as for these crashes the police does not attend the crash site, only an ambulance does. Therefore, the number of bicycle crashes is underrepresented in crash data based on police reports. This may lead to biased coefficients and possibly also affects the coefficient of exposure to cyclists in the present study, making it less interpretable (Derriks & Mak, 2007; Wegman et al., 2012). A solution to handle the underreporting is to link several data sources, for example police reports and hospital data. Another solution could be to use ambulance reports in addition to police reports. A pilot study with a sample of the ambulance data from the Netherlands, which matched Dutch police reported data with ambulance reported data, showed that in 2018 in the Province of Utrecht there were around three times as much people attended by an ambulance than the police reports showed (Olij & Nijman, 2020). Therefore, including crash data based on ambulance reports would be preferable, as they give a more complete picture of the safety problem for cyclists. Unfortunately, the ambulance data for the study area are still unavailable. Hopefully, future studies are able to include such data in order to achieve more complete conclusions about cyclist safety. Nevertheless, the police reported data used in this paper are still a good representation of the overall crash patterns as there is no selective reporting and underreporting is homogeneous.

Lastly, the analysis in this paper is based on one city. This makes it difficult to generalise the results to other locations. It is therefore suggested to expand this study to other cities in and outside the Netherlands to confirm the findings. Moreover, as the present study aimed solely on identifying the effect of hourly variation in exposure to cyclists and motorised vehicles on bicycle crashes, the whole network was aggregated and treated as a single entity. Because geometric characteristics of the road network do not vary over the hours of the week, they were excluded from the analysis as the focus was only on the temporal variation in the exposure variables. Future studies may investigate both temporal and network-wide variation in crashes in relation to exposure to traffic by also disaggregating the network. The findings can be compared with the present study in order to understand how treating the network as a single entity affects the estimates compared to analysing each road section as a separate entity. In such studies, geometric characteristics and other factors affecting bicycle crash frequency can be included. Additionally, disaggregating the network may also deal with the issue of autocorrelation as discussed in Section 4.3.

7. Conclusions

This paper tried to answer the research question: “How does hourly variation in exposure to cyclists and motorised vehicles affect cyclist safety?” The answers to this question are formulated as the following main conclusions, which refer to the hypotheses from Section 2.3:

1. Bicycle crash frequency increases less than proportional with an increase in the exposure to cyclists and more linearly with an increase in the exposure to motorised vehicles.
2. Peak hours have the highest levels of the total network exposure, which consequently leads to higher numbers of bicycle crashes.
3. In absolute numbers, cyclists are more involved in crashes during the day than during the evening and night. However, after correcting for exposure, the evening and night hours are more unsafe than the daytime hours.
4. Bicycle crashes on 50 km/h roads are more sensitive to an increased exposure to motorised vehicles than bicycle crashes on 30 km/h roads.
5. Separated facilities are found to be safer than on-street cycling facilities given the motorised vehicle volumes.

The utilised approach was suitable to answer the research question, as it showed how exposure affects bicycle crash frequency on a highly detailed temporal resolution. Furthermore, the fourth conclusion supports the ongoing discussion in Europe about decreasing the speed limit on 50 km/h urban roads to 30 km/h. However, as exposure levels are lower and the layout of 30 km/h roads is different to 50 km/h roads, it takes more than only decreasing the speed limit to realise a reduction in bicycle crashes. Moreover, the fifth conclusion shows there is a need to separate cyclists from motorised vehicles, especially on distributor roads. Finally, it is clear that cycling and driving will increase in the future due to population growth. This increase will cause safety issues for all types of road users including drivers, cyclists, and pedestrians. Accordingly, this study shows that road safety for cyclists needs further improvements, as cycling in cities keeps increasing.

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Predicted bicycle crashes and 68% prediction interval
Fig. A.1. Predicted bicycle crashes and 68% prediction interval for 50 km/h roads.

Fig. A.2. Predicted bicycle crashes and 68% prediction interval for 30 km/h roads.

Fig. A.3. Predicted bicycle crashes and 68% prediction interval for 50 km/h roads with separated bicycle facilities.
Fig. A.4. Predicted bicycle crashes and 68% prediction interval for 30 km/h roads with separated bicycle facilities.

Fig. A.5. Predicted bicycle crashes and 68% prediction interval for 50 km/h roads with on-street cycling facilities.

Fig. A.6. Predicted bicycle crashes and 68% prediction interval for 30 km/h roads with on-street cycling facilities.
Appendix B. Difference between actual crashes and predicted crashes

Fig. B.1. Difference between actual crashes and predicted crashes for 50 km/h roads.

Fig. B.2. Difference between actual crashes and predicted crashes for 30 km/h roads.
Fig. B.3. Difference between actual crashes and predicted crashes for 50 km/h roads with separated bicycle facilities.

Fig. B.4. Difference between actual crashes and predicted crashes for 30 km/h roads with separated bicycle facilities.
References


